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Role of environmental regulation and renewable energy technology innovation in carbon neutrality: A sustainable investigation from China

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ABSTRACT

With global climate change posing a major threat to human society, many countries have elevated "carbon neutrality" to a national strategy and put forward a vision of a zero-carbon future. In this process, environmental regulation (ER) and renewable energy technology innovation (RET) are important factors that contribute to achieving the carbon neutrality goal. Thus, this study employs a spatial econometric technique model to investigate the direct and indirect effects of ER and RET on environmental sustainability from both theoretical and empirical dimensions based on panel data of 30 Chinese provinces during 1998–2020. The results show that ER is not conducive to the improvement of environmental quality in local and neighboring areas, but it is beneficial to the reduction of CO_2 emissions when the level of economic development is greater than the critical threshold of 9.126, i.e., the "inverted U-shaped" curve relationship. On the contrary, RET has a beneficial impact on the environment, but when the economic development level is greater than the critical threshold of 8.790, the carbon reduction effect of RET is reduced. Thus, the significance and magnitude of the carbon reduction effect of ER and RET depend on the regional economic development level, and excessive RE will have a suppressive effect on RET. The paper assisted policy makers in designing a holistic policy to enhance environmental sustainability through ER and RET, especially in the Chinese region.

1. Introduction

Global warming has been indisputable in recent years due to worldwide energy depletion, environmental degradation and climate change, and green sustainability has clearly grown into a critical focus of attention for many countries [1]. Since industrialization, human beings have escalated their development needs and greenhouse gas emissions have become increasingly robust. Long-term studies have shown a sharp increase in CO_2 concentrations starting in the early 19th century, a point in time right around the industrial revolution [2,3]. Currently, CO_2 is considered one of the most potent pollutants in terms of greenhouse effect, while elevated CO_2 concentrations are closely related to climate change [4,5]. Accordingly, in the context of globalization, environmental pollution poses a serious threat to the ecological environment in the process of economic development in various countries. Similarly, China is facing this problem of deteriorating environmental quality [6]. In the past forty years of innovation and development, China has achieved remarkable economic growth and greater success in economic development, and the demand for resources for residents' living and production has increased rapidly [7,8]. In this process, resources, environment and social systems have developed rapidly, and problems such as energy shortage and serious environmental pollution have gradually emerged, making the contradiction between economic development and resources and environment more and more prominent, prompting air pollution, water pollution and soil pollution to be a serious threat to the production and life of residents [9]. However, the phenomenon of hazy weather frequently occurs in some areas of China, and the phenomenon of water pollution and soil pollution is becoming increasingly serious. In addition, environmental pollution emissions have chronic effects on human health, agricultural crop yields, forestry, fish and construction materials, such as air pollution induces respiratory diseases, and water and soil pollution endangering food safety and human health.

With the massive emission of greenhouse gases (mainly CO_2), the quality of life of the world's people and the economic growth of all regions are being seriously challenged [10]. According to the latest

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statistical report released by the International Energy Agency (IEA), global CE will exceed 36.3 billion tons in 2021, an increase of 6% compared to 2020, a record high, due to extreme weather and energy demand. As the largest developing country, China's total CE exceeded 6.99 billion tons in 2007, surpassing the United States for the first time and ranking first in the world. According to the latest statistics from Carbon Brief, by 2021, China's total CE will be nearly 11.9 billion tons, accounting for one-third of the world's total emissions. In the Environmental Performance Index (EPI): 2016 Report, China ranks 160th in the EPI, down 40 spots from 2018, making it the "hardest hit" in terms of pollution overload, reflecting the enormous pressure on the ecological environment caused by China's rapid economic development. Therefore, in today's deepening globalization, the Chinese government urgently needs to solve the problems of "adjusting structure", "promoting transformation", "preventing pollution" and "reducing emissions" through relevant policy instruments. To achieve green and sustainable growth, the government of China has introduced a number of laws, regulations and policies to regulate the environment [11]. The words "green" and "ecology" are repeatedly included in Xi's Report to the 19th Communist Party of China National Congress. The search for technological innovations and breakthroughs in energy and environmental protection has become an important tool for the Chinese government to achieve this goal. Are the current ER effectively reducing CE? What is the effect of renewable energy technology factors on CE? Does CE have a counterproductive effect on the interaction between ER and RET? Does the interaction between ER and RET have an adverse effect on CE? The responses to the questions above are of importance to low-carbon pilot work, low-carbon development support systems and national efforts to address climate change.

In this context, this study assesses the impact of ER and RET on environmental sustainability in various regions of China using annual data from 1998 to 2020. The results of this study can help Chinese regions achieve their carbon neutrality goals by strengthening ER and policy development and improving renewable energy technology capacity. The contributions of this paper based on literature combing and theoretical analysis are as follows. Firstly, we explore whether ER are conducive to CE reduction and analyze whether ER will achieve CE reduction through RET from the perspective of spatial analysis. Secondly, the extent to which ER promotes RET and how they are related to CE reduction deserves further exploration. Thirdly, based on the regional heterogeneity of ER, we explore whether there are also regional variations in the effect of RET on CO_2 reduction under the role of ER. Finally, does the stronger ER accelerate the innovation of renewable energy technologies in the region and thus promote CE reduction? Therefore, clarifying these questions can, to some extent, help promote international cooperation on CE reduction technologies and low-carbon environmental protection, while providing an important reference for achieving the carbon neutrality target.

2. Literature review

Carbon emissions, as the main source of greenhouse effect, have been of great interest to researchers around the world. Many studies have been done in recent years by researchers in energy, environment and society on the drivers of CE such as ER and technological innovation (TI), but the findings vary greatly due to different time dimensions, countries or regions, and econometric methods. Thus, this section is dedicated to summarizing and reviewing the relevant literature on the effects of RE and TI on environmental pollution (CE) in different national, regional and temporal dimensions based on a global perspective.

2.1. The relationship between environmental regulation and CO_2 emissions

Along with the accelerating industrialization and urbanization, the total amount of polluting gases and the intensity of emissions are also gradually strengthened, and the greenhouse gases led by CO_2 pose a serious threat to human existence through environmental changes. As an important means to solve the current environmental pollution problem and an essential way to realize economic and social sustainable development, ER has been attracting the attention of experts and scholars in recent years. Currently, the research on the link between ER and CE is mainly based on the "green paradox" and the "forced emission reduction". Scholars who hold the "green paradox" view argue that the effect of ER is a negative "regressive effect" on CE [12–17]. However, researchers with a "forced emission reduction" perspective consider the effect of ER on CE as a positive "anti-driving effect" [18–20]. Moreover, different aspects have been studied by other researchers. For example, Wang et al. (2020a) [21], examine the overall efficacy of feedback mechanisms for various types of environmental climate policies to illustrate the "lag effect" and "backfire effect" of current policy instruments [22–24]. analyzed the dual impact mechanism of ER on CE and found that the impact trajectory of ER on CE showed an inverted "U-shaped" curve. In other words, with increased ER (tighter environmental policies), CE levels show an "upward-downward" trend, i.e., it shows the "green paradox" effect before the inflection point, and the "emission reduction effect" after the inflection point [25]. However [26,27], found spatial heterogeneity between ER and CE in different national, regional and urban frameworks by analyzing the pathways of ER on CE. In other words, the effect of ER on CE has different intensities in different scenarios, i.e., developing countries (regions) $>$ developed countries $>$ less developed regions.

2.2. The relationship between technological innovation and CO_2 emissions

Given the externalities of environmental pollutant emissions (CE) and the public goods nature of the environment, the CE problem can hardly be effectively solved by market mechanisms alone. Therefore, ER becomes a powerful breakthrough to remedy market failures and address environmental problems. However, in the long run, to effectively solve the carbon emission problem, technological progress, especially green technology-oriented innovation, is required [28,29]. However, in the existing studies, the academic community has not yet reached a unified conclusion and understanding on the impact pathway of the CO_2 emission effect of technological innovation. For example [30], by examining the application of Best Available Technology (BAT) in the regulation of emissions from coke plants under the EU Industrial Emissions Directive (IED), and they concluded that it significantly contributed to CE reduction [31]. Based on this [32], conducted a relevant study for Mexico, who concluded that TI tends to curb CE and supports the environmental Kuznets curve (EKC) hypothesis [33]. assessed the effects of environmental technology innovation on CE in 30 Chinese provinces from 2000 to 2013 in four different dimensions: performance of innovation, resource of innovation, intellectual innovation and environment of innovation, and they concluded that ET innovation can effectively reduce local CE [34]. [35]; in assessing the impact of innovations in BRI countries on CE from 1979 to 2019, confirmed that efficient TI helps to reduce CE from production processes or other economic activities [36]. reached the same conclusion in their assessment of the impact pathways of TI on energy efficiency and emission mitigation in China over the period 2005–2016, but they were surprised to find that the impact of innovation in technology on CE is also constrained on energy consumption, and if the energy consumption surpasses a critical value, a catalytic role of TI on CE reduction would be converted into a suppressive one, to the detriment of mitigation quality improvement. However [37,38], proposed the opposite view, and they argued that the CE effect of TI has a certain time lag and spatial heterogeneity. TI, especially green technology innovation, has done little to mitigate CO_2 pollution in highly developed regions, whereas it has significantly reduced CE in underdeveloped regions. In addition [39], examined the cyclical impact of green and sustainable technologies on CE in BRICS countries from 1990 to 2018. They were surprised to find that the link between green and sustainable technologies and CE was counter-cyclical and not conducive to CE reduction at the initial stage [40]. used a spatial econometric model to examine the effect of technology innovation in green technology on CE efficiencies in 285 cities in China from 2011 to 2017, and they concluded that the synergistic impact of TI in green technology played an essential part in promoting CE efficiency in the city, but suppressed CE efficiency in neighboring cities to some extent. Given that, Demircan Çakar et al. (2021) supported this view in a study of eight developing countries and six developed countries, where they concluded that the level of TI has a positive impact on CE from transport, and this impact effect is more significant in developed countries. In summary, since TI may increase or decrease CE, does it then stem from the fact that a bi-directional dynamic link exists for TI and CE?

2.3. The relationship between environmental regulation and technological innovation

In recent years, the relationship between ER and TI has gradually become a hot spot for academic research as the environmental pollution problem has become more and more serious. Neoclassical economic theory suggests that strict ER has a "crowding-out effect" on TI, raising the cost of pollution and crowding out funds for innovation activities [41]. In contrast, the "Porter hypothesis theory" argues that moderate ER in the long run will stimulate firms' TI activities and compensate for the additional costs of regulation, thus creating an "innovation compensation effect" [42,43]. Since TI is a process activity, more and more researchers have started to study the effect of ER from a systems perspective on the efficiencies of TI. Among them, some researchers argue a positive effect of ER on the efficiency of TI, which to some extent greatly contributes to the generation of TI [44–47], while others argue a "crowding-out effect" of ER on TI productivity [48–50]. Besides the above two views, the non-linear nature ascribed to the effect of ER on the efficiency of TI is a more common conclusion among academics in recent years. For example [51], employed a fixed-effects model for examining the link between TI and ER for Chinese industrial firms from 2008 to 2016, which found a "U-shaped" link between the intensity of ER and firm TI that first decreases and later increases. Similarly [43], reach similar conclusions by using a dynamic spatial panel model. However, However, Wang et al. (2020b) and [52] suggest the opposite, arguing that ER has an inverted "U-shaped" curvilinear relationship on the path of firms' green technology innovation. Accordingly [53], examined the effect of ER on TI for the Chinese coal-fired power industry from 2008 to 2017 by constructing a mediating effects model, which found a "U-shaped" curve of the effect of ER intensity on TI efficiency.

In summary, we can infer that the existing literature has reasonably discussed and elaborated the connection of ER, TI, especially green technology innovation, and CE, but there are few works that explore the role of energy technology innovation on CE in the framework of environmental regulation, especially the possible RET, since it is fundamental to develop renewable energy as a way to reduce CE. Therefore, studying the CE of RET is important for achieving global regional sustainable development, and is conducive to achieving "carbon peaking" and "carbon neutrality" on a global scale. However, the role of CE from ER and TI (environmental technology innovation, green technology innovation) in most literature studies has ignored the spatially heterogeneous effects of CO_2. It would thus be reasonable to justify the present study as a contribution to the existing literature to fill the gaps of current research.

3. Materials, methods and data

3.1. Spatial spillover econometric model

To effectively investigate the heterogeneous influences of ER and RET on per capita CE in China, this study builds a basic panel data model following the STIRPAT model proposed by Dietz et al. (1997). This model mainly emphasizes the drivers that influence the greenhouse effect: population, affluence, and technology, etc [54]. In addition, we extend the STIRPAT model according to the approach presented by Ref. [55] to include ER, RET, Pgdp, URB, IND, and ISU in the same research framework, and construct the basic regression equation as follows:

$$lnCE_{it} = \beta_0 + \beta_1 lnER_{it} + \beta_2 lnRET_{it} + \beta_3 Pgdp_{it} + \beta_4 URB_{it} + \beta_5 lnIND_{it} + \beta_6 ISU_{it} + \varepsilon_{it} \tag{1}$$

where CE denotes per capita CO_2 emissions; ER denotes environmental regulation; RET denotes renewable energy technology innovation; Pgdp indicates economic growth (GDP per capita); URB, IND indicates urbanization and industrialization, respectively; ISU denotes industrial structure upgrading; i, t represent panel city i (30 provinces) and time t (years), respectively; $\beta_1 \ldots \beta_6$ represents estimated coefficients, and ε_{it} denotes random disturbance terms.

As illustrated by the studies of [56–58]; with the continuous development of global economic integration, the environmental quality of a region is influenced not only by the affluence and economic structure of the region, but also by the socio-economic factors of the surrounding areas. Therefore, to better reflect the spatial correlation of CE among different regions, three spatial econometric models were constructed in this study: the SAR, SEM and the SDM model. However, each spatial econometric model has different paths of action, as shown in the following models.

$$lnCE_{it} = \beta_1 lnER_{it} + \beta_2 lnRET_{it} + \beta_3 lnPgdp_{it} + \beta_4 lnURB_{it} + \beta_5 lnIND_{it} + \beta_6 \ln ISU_{it} + u_i + \varepsilon_{it} \tag{2}$$

$$lnCE_{it} = \beta_1 lnER_{it} + \beta_2 lnRET_{it} + \beta_3 \ln Pgdp_{it} + \beta_4 \ln URB_{it} + \beta_5 lnIND_{it} + \beta_6 \ln ISU_{it} + u_i + \varepsilon_{it}, \varepsilon_{it} = \lambda \sum_{j=1}^{n} W_{ij}\varepsilon_{it} + v_{it} \tag{3}$$

$$lnCE_{it} = \rho \sum_{j=1}^{n} W_{ij} lnCE_{it} + \beta_1 lnER_{it} + \beta_2 lnRET_{it} + \beta_3 \ln Pgdp_{it} + \beta_4 lnURB_{it} + \beta_5 lnIND_{it} + \beta_6 \ln ISU_{it} + u_i + v_{it}, v_{it} = \lambda \sum_{j=1}^{n} W_{ij}\varepsilon_{it} + \varepsilon_{it} \tag{4}$$

$$lnCE_{it} = \alpha_i + \rho \sum_{j=1}^{n} W_{ij} lnCE_{it} + \beta_1 lnCE_{it} + \beta X_{it} + \gamma_1 W \times lnCE_{it} + \gamma \sum_{j=1}^{n} W_{ij} X_{it} + \varepsilon_{it}, \varepsilon_{it} = \lambda W v_{it} + \varepsilon_{it} \tag{5}$$

where, equation (1) is the SAR model containing the spatial lag term of industrial upgrading, equation (2) is the SEM model with spatial dependence transmitted through the error term, equations (1) and (2) are combined into equation (3) SAC model, and equation (4) is the SDM model, which can combine the characteristics of SAR model and spatial lag model (SLM) and OLS. In addition, ρ, λ and γ denotes the spatial lag coefficients, spatial error coefficients and spatial coefficients, respectively; W_{ij} denotes the spatial weight matrix.

For the spatial weight matrix W_{ij}, it constructs the spatial weight matrix with the decaying changes of spatial geographic adjacency or not and geographic distance, which can not only include the objective fact that the economic activities between regions weaken with increasing distance, but also encompass the correlation dynamics between regions that are non-adjacent but closer and more influential. Therefore, when the spatial adjacency weight matrix, i.e., if two regions are adjacent (with a common border), the corresponding element of the weight matrix takes 1, otherwise 0; the spatial weight matrix of geographic distance, i.e., if two places are not adjacent (without a common border), the corresponding weight is the inverse of the distance between the provincial capitals or central locations of *i* and *j* regions, otherwise 0.

$$\sum_{j=1}^{n} W_{ij} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & & & \\ w_{n1} & w_{n2} & \dots & w_{nn} \end{bmatrix}$$

3.2. Variables and data sources

3.2.1. Explained variable

CO_2 emissions (CE): Since no official CE data are available for Chinese provinces, municipalities and autonomous regions, this study draws on the method used by Refs. [59,60] to calculate CE and the method recommended by the *2006 IPCC National Greenhouse Gas Guidelines* to calculate CE for Chinese provinces. The specific algorithm is to convert the end-use energy consumption into tons of standard coal uniformly through the discount factor of standard coal. The CE is then calculated using the CE conversion formula. Thus, the specific formula for calculating CE from end-use energy consumption (primary energy) is as follows.

$$CE = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n} E_i \times NCV_i \times CEF_i \times \frac{44}{12} \tag{6}$$

where, *C*E denotes the total carbon dioxide emission during the consumption of each type of energy; C_i denotes the CE of the *i*-th energy source; E_i denotes the consumption of the *i*-th energy source; NCV_i denotes the average low level heat generation; CEF_i denotes the CE factor of the *i*-th energy source.

3.2.2. Core explanatory variables

Environmental regulation (ER): ER inevitably affects changes in firms' production processes, resource reallocation, capital investment, labor intensity and technological innovation, which in turn trigger changes in ecological and environmental factors. This study draws on the methodology of [43] to measure environmental regulation, which is calculated as follows:

Firstly, the emissions of pollutants (wastewater, SO_2, and soot) were linearly normalized across provinces.

$$US_{ij}^{s} = \left[UE_{ij} - min\left(UE_j\right)\right] / \left[max\left(UE_j\right) - min\left(UE_j\right)\right] \tag{7}$$

where, US_{ij}^{s} indicates the standardized value of the index; UE_{ij} indicates the unit output pollutant emissions of pollutant *j* in province *i*; $max(UE_j)$ and $min(UE_j)$ are the maximum and minimum values of each indicator in 30 provinces.

Secondly, since the pollutant emissions and the intensity of emissions of each pollutant vary greatly among provinces, the adjustment factor is used to approximate the differences in pollutant characteristics. The formula for calculating the adjustment factor is as follows:

$$W_j = UE_{ij} / \overline{UE_{ij}} \tag{8}$$

where, $\overline{UE_{ij}}$ is the provincial average of emissions per unit output of pollutant j during the sample period.

Finally, we calculate the level of intensity of ER in each province using the weighting method.

$$ER_i = \frac{1}{3} \sum_{j=1}^{3} W_j UE_{ij}^{s} \tag{9}$$

where, ER_i represents the level of ER intensity in province i.

Renewable energy technology innovation (RET): Based on the endogenous economic growth theory, the more developed the economy is, the greater the enterprises' investment in R&D and innovation of renewable energy technologies, which is conducive to the gathering of talents and the overflow of new technological knowledge, thus optimizing industrial processes and accelerating the speed of clean technology development. Therefore, RET promotes energy clean transition from the energy structure, carbon productivity improvement from the production process, and industrial structure decarbonization from the meso perspective, which in turn promotes carbon emission reduction through the above three mechanisms. In addition, this research measures the number of renewable energy patents, wind power patents, solar PV patents and ocean energy patents in four dimensions based on the availability of data. In general, with higher levels of RET, the lower the level of CE, which is more favorable to achieve carbon attainment and carbon neutrality.

3.2.3. Control variables

Environmental sustainability is influenced by many things besides ER and RET, such as the level of Pgdp, URB, IND and ISU. To avoid the bias of other uncontrollable factors on the results, this study introduced relevant potential influence variables to control for them: (1) Economic development level (Pgdp): taking into account the impact of differences in economic development levels among regions on CE, this study uses GDP per capita to be a surrogate variable for economic level of development. (2) Urbanization (URB): The process of urbanization is not only the process of transformation of the rural population to the city in the traditional sense, but also includes the transformation of production and lifestyle, such as the application of more advanced technology, cleaner energy and a more rational way of living. Therefore, the ratio of urban population to total population is used as a measure in this study. (3) Industrialization (IND): Industrial activities are the main reason for the dramatic increase in CE in the context of globalization. The higher the proportion of urban industry in the primary, secondary and tertiary sectors, the greater the percentage of companies using fossil energy, which then leads to increased total urban CE. Thus, according to Refs. [36,59]; the share of the output value of the secondary industry in GDP is used in this study to measure. (4) Industrial Structure Upgrading (ISU): Regional industrial structure upgrading emphasizes the replacement of leading industries (industrial structure heightening) and rational allocation among industries (industrial structure rationalization) in each region based on the dynamic changes of its resource factor endowment structure. Therefore, this study takes the value added of tertiary industry to value added of secondary industry as a measurement, i.e., a larger index means a more optimized industrial structure.

3.2.4. Data sources and descriptive statistics

In this study, we select panel data of 30 Chinese provinces, municipalities directly under the Central Government and autonomous regions (except Hong Kong, Macau, Taiwan and Tibet due to missing data) from 1998 to 2020 as the data set for analysis. Among them, the initial data of regional development level (GDP per capita), RET, URB, IND and ISU are obtained from the "China Economic and Social Development Statistical Database" on China Knowledge. The original data for the variables of ER and CE were obtained from China Statistical Yearbook and China Environmental Statistical Yearbook. Some missing data were supplemented by the China Energy Statistical Yearbook, China Urban Statistical Yearbook, and China Science and Technology Statistical Yearbook. In addition, considering data heteroskedasticity and applicability, this study takes natural logarithmic values for the selected variables. For all data on monetary values, this study adjusts the relevant indicators with the year 2000 as the base period constant price. Table 1 gives the list, description and sign of the selected variables, while Table 2 gives the

Table 1
List of variables, description and symbols.

Variable types	Variables	Symbol	Definitions
Dependent variable	CO_2 emissions	CE	CO_2 emissions measured as metric tons per capita
Independent variables	Environmental regulation	ER	Total wastewater discharge to total industrial output ratio
			Ratio of SO_2 emissions to total industrial output value
			Integrated industrial solid waste utilization rate
	Renewable energy technology innovation	RET	Number of renewable energy patents
			Number of wind power patents
			Solar Photovoltaic Patents
			Marine Energy Patents
Control variables	Economic growth	Pgdp	Total GDP/total population
	Urbanization	URB	% of total population
	Industrialization	IND	% of GDP
	Industrial structure upgrade	ISU	Tertiary sector added value to secondary sector added value ratio

descriptive statistics of the data for each variable. Table 2 results show that the mean values of all the selected variables are positive except for ER, but the variability (volatility) of economic growth is the greatest relative to the other selected variables. Moreover, according to the Jarque-Bera test, all variables are normally distributed at the 5% level of significance. Similarly, the results of the VIF test also verify this hypothesis and none of them has the problem of multicollinearity, due to the fact that the variance expansion coefficients of the selected variables are all less than the empirical criterion of 10.

4. Results and discussion

4.1. Spatial autocorrelation test

Before conducting spatial econometric tests, spatial autocorrelation analysis needs to be used to test whether variable indicators are spatially autocorrelated or spatially dependent to improve the accuracy, veracity and reliability of the test results. Therefore, drawing on Moran (1995), this study uses Moran's I index to test the autocorrelation of CE, ER, and RET, respectively. Table 3 gives the local Moran's I estimates based on the geographical proximity matrix for CE, ER and RET for 30 Chinese provinces for the period 1998–2020. The estimation results in Table 3 show that the overall local Moran's I estimates are positive at the 1%, 5%, and 10% significance levels, and that this geographic (spatial) correlation becomes more significant over time, followed by a slight decrease, except for RET. This suggests that the current Chinese CE, ER and RET are not completely random geographically, but have a significant spatial dependence. In addition, to test the accuracy and reliability of the results, this study also examined the spatial clustering of CE, ER and RET in 30 Chinese provinces and plotted Moran scatter plots for 1998, 2005, 2013 and 2020 as well as analyzed their local spatial correlations (see Figs. 1–3). The Moran scatter plots of CE, ER and RET in 1998, 2005, 2013 and 2020 are given in Figs. 1–3, respectively. According to Figs. 1–3, the change of the map divides the CE, ER and RET of 30 Chinese provinces to four aggregation patterns: high-high (H–H) aggregation surrounded by cities of the same high-level in the surrounding area, low-high aggregation (L-H) surrounded by low and high levels, low-low aggregation (L-L) surrounded by low-level, and high-low agglomeration (H-L) is surrounded by high and low level provinces and cities. From the figure, it can be seen that CE, ER and RET in most Chinese provinces are in the H–H aggregation area and L-L aggregation area in 1998, 2005, 2013 and 2020, which indicates that they have obvious spatial autocorrelation.

4.2. Spatial measurement model inspection and selection

Since many spatial econometric models are available, this study performs the LM test, Wald test and LR test in turn to be selected as the most appropriate spatial model before performing model estimation (see Table 4). Table 4 estimation results show that both LM-Lag statistic and LM-Error statistic under geographically adjacent weight matrix are significant at 5% significant level, i.e., the original hypothesis of explanatory variables is rejected without any spatial lag and spatial autocorrelation error. However, the R-LM-Error statistic is not significant at the significance level and has a relatively small p-value, making the use of spatial SEM more appropriate than SAR. In addition, the original hypotheses of the Wald test and LR test were also rejected at the 5% confidence level, making the spatial Durbin panel data model (SDM) the most suitable spatial panel data model.

4.3. Benchmark results

On the basis of previous spatial correlation tests, we find that there exists a long-term stable positive region-wide correlation and dependence of CE, ER and RET across regions in China, and there is a positive agglomeration of local spatial correlations. To further investigate the

Table 2
Descriptive variable statistics and correlation analysis.

Variables	lnCE	lnER	lnRET	lnPgdp	lnURB	lnIND	lnISU
Mean	1.970	−1.169	6.633	10.085	3.806	3.628	4.615
Median	1.921	−1.087	6.619	10.232	3.832	3.634	4.596
Max	4.282	1.282	11.166	12.719	4.495	4.639	6.272
Min.	0.136	−4.724	0.000	7.761	2.682	2.271	3.183
Std. dev.	0.713	0.916	2.020	0.958	0.365	0.305	0.454
Skewness	0.330	−0.434	−0.052	−0.094	−0.272	−0.214	0.325
Kurtosis	3.239	3.660	2.461	2.312	2.622	6.134	5.531
Jarque-Bera	14.144 (0.001)	34.169 (0.000)	8.662 (0.013)	14.616 (0.001)	12.617 (0.002)	28.758 (0.000)	19.640 (0.000)
Obs.	690	690	690	690	690	690	690
Correlation matrix							
CE	1.000						
ER	0.161***	1.000					
RET	0.121***	−0.394***	1.000				
Pgdp	0.358***	−0.490***	0.801***	1.000			
URB	0.403***	−0.241***	0.595***	0.736***	1.000		
IND	−0.001	−0.145***	0.219***	0.222***	0.255***	1.000	
ISU	0.152***	0.060	0.280***	0.176***	0.293***	−0.357***	1.000
VIF	1.927	1.321	3.038	4.623	1.513	2.629	1.879

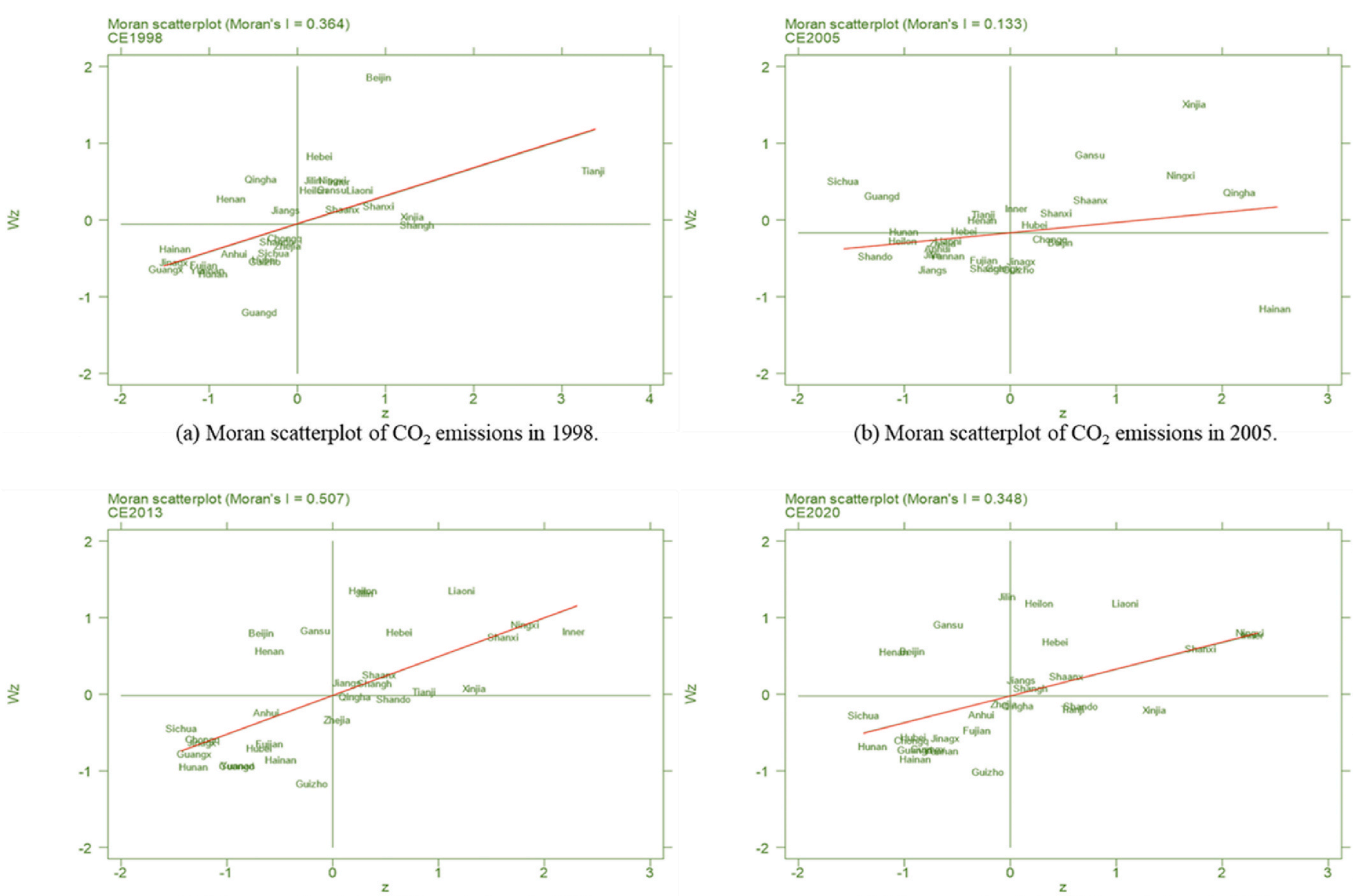
Notes: p-values are given in parentheses; *** represents significance at the 1% level.

Table 3
Moran index based on geographic adjacency matrix.

Year	Carbon dioxide (CE)		Environmental regulation (ER)		Renewable energy technology innovation (RET)	
	Moran's I Value	Z value	Moran's I Value	Z value	Moran's I Value	Z value
1998	0.364***	3.408	0.011	0.393	0.041	0.626
1999	0.420***	3.830	0.064	0.816	0.029	0.520
2000	0.087	0.992	0.030	0.554	0.067	0.831
2001	0.147*	1.469	0.097	1.131	−0.025	0.080
2002	0.143*	1.440	0.214**	2.037	−0.032	0.017
2003	0.134*	1.371	0.054	0.721	0.062	0.785
2004	0.127*	1.322	0.394***	3.459	0.035	0.561
2005	0.133*	1.372	0.060	0.762	0.122*	1.263
2006	0.356***	3.152	0.138*	1.407	0.109	1.159
2007	0.471***	4.078	0.169**	1.661	0.130*	1.325
2008	0.504***	4.340	0.189**	1.825	0.129*	1.321
2009	0.488***	4.211	0.251***	2.328	0.171**	1.659
2010	0.489***	4.226	0.119*	1.253	0.178**	1.722
2011	0.449***	3.920	0.101	1.095	0.184**	1.767
2012	0.474***	4.116	−0.009	0.207	0.199**	1.894
2013	0.507***	4.357	0.129*	1.326	0.218**	2.047
2014	0.495***	4.273	0.157*	1.583	0.216**	2.027
2015	0.477***	4.120	0.090	1.021	0.217**	2.025
2016	0.429***	3.740	0.162**	1.623	0.233**	2.149
2017	0.416***	3.634	0.105	1.128	0.213**	1.997
2018	0.406***	3.562	0.122*	1.268	0.248**	2.268
2019	0.401***	3.536	0.107	1.163	0.242**	2.220
2020	0.348***	3.109	0.042	0.625	0.275***	2.486

Note: ***, **, and * denote that the coefficient of the variable has adopted the significance test of 1%, 5%, and 10%, respectively.

effects of environmental regulation and RET on CE and to ensure the reliability and accuracy of the regression results, we therefore constructed SEM, SAR and SDM models and analyzed them from the perspectives of direct and indirect impact effects and total impact effects (see Table 5). In Table 5, first we build the fixed effects (FE) model based on the Hausman test and give the fixed effects regression results. Model 1 shows that ER, URB, and ISU have positive effects on CE at 1% and 5% significance levels, respectively, indicating that CE are not currently peaking in all regions of China [6]. Specifically, when Pgdp, URB and ISU increase by 1%, CE will increase by 0.416%, 0.378% and 0.286%, respectively. At the same time, this is the main reason why the path of ER on CE in each region of China is an "inverted U-shaped" curve of promotion followed by suppression. In the upward phase of the "inverted U", CE increases as the intensity of ER increases. In this phase, the "green paradox" effect is dominant. On the contrary, in the downward phase of the "inverted U-shape", CE decreases as the intensity of ER increases, and in this phase, the "forced emission reduction" effect is dominant [22–24,52]. From the above results, it is clear that, overall, a certain "forced emission reduction" effect can be observed with the increase in the intensity of ER without affecting the current level of regional economic development in China [25]. However, the results also found a significant negative effect of RET and IND on CE, i.e., a 1% increase in RET and IND would reduce CE by 0.064% and 0.115%, respectively. This indicates that the increase in the level of RET and industrialization is beneficial to the improvement of environmental quality [33], but the IND is statistically weakly significant at 10% level of significance, so the regional industrialization development is negligible in reducing CE. This finding is contrary to Ref. [39] for BRICS countries and [61–64] for China, who concluded that green RET promoted the increase of CE without affecting economic development, but



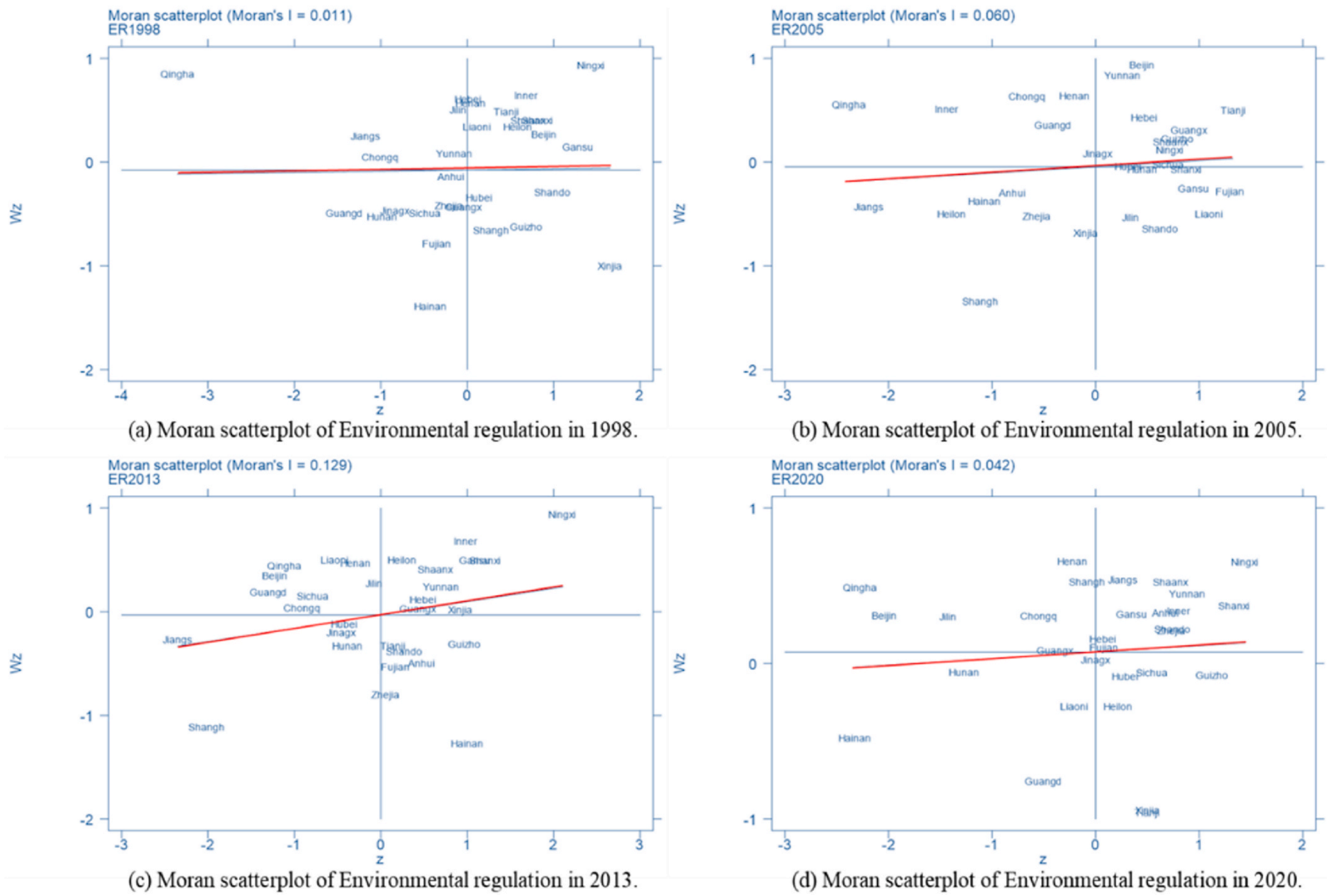
(a) Moran scatterplot of CO_2 emissions in 1998.

(b) Moran scatterplot of CO_2 emissions in 2005.

(c) Moran scatterplot of CO_2 emissions in 2013.

(d) Moran scatterplot of CO_2 emissions in 2020.

Fig. 1. Moran scatterplot of CE.



(a) Moran scatterplot of Environmental regulation in 1998.

(b) Moran scatterplot of Environmental regulation in 2005.

(c) Moran scatterplot of Environmental regulation in 2013.

(d) Moran scatterplot of Environmental regulation in 2020.

Fig. 2. Moran scatterplot of ER.

had no significant impact on less developed regions [65]. With the increase in the intensity of ER, the increase in economic levels, such as economic growth, urbanization, industrialization and industrial structure upgrading have promoted ET innovation, especially green and clean RET [43]. This also reduces the proportion of fossil fuel consumption in urban industrial production, thus increasing the efficiency of regional industrial production in China and reducing the consumption of industrial materials, and further curbing the increase of industrial carbon emissions. Thus, ER can negatively influence CE performance through RET to achieve emission reduction targets [66].

Second, to explore the effects of ER and RET on CE within a regional economic development framework for local and surrounding areas, SEM, SAR and SDM models were constructed to consider the effects of geographic position for economic activities. For this reason, based on the above estimation results, we then chose to discuss and analyze them on the basis of the SDM. The SEM, SAR and SDM estimation results are given in models 2–4 in Table 5, respectively. The SDM based on the general form of SEM and SAR models can fully consider the joint effect of spatially lagged ER and RET as well as spatially lagged regional carbon emissions per capita on carbon emissions per capita, because it can provide unbiased estimates, and the spillover effects of ER and RET can be better observed during the estimation process [59]. According to the SDM estimation results of model 4, the coefficients of the effects of ER and RET on local CE are 0.061 and 0.128, respectively, and are significant at the 5% level of significance. This indicates that the local CE will increase by 0.061% and 0.128% when the ER and RET increase by 1%. In addition, the spatial spillover effect of ER on local CE ($W_x \times \ln ER$) has a coefficient of 0.085 and the spatial ρ or spatial λ of both spatial econometric models are significantly positive at 1% significance level, which indicates that the increase in the intensity of ER is not conducive to the improvement of environmental quality, but exacerbates the environmental pollution in local and neighboring areas. Apparently, the growth of CE in neighboring provinces depends on the "contribution" of local ER, and the development of ER (rules and regulations) between regions imitates each other's behavior, i.e., the ER behavior in one region is "contagious" to the neighboring regions. On the other hand, provinces with higher levels of economic development will have a "siphon effect" or "return effect" on neighboring regions (which are usually low economic provinces or underdeveloped cities) and will induce labor and enterprises to move to the region as a whole. This will lead to a region-wide migration of labor and enterprises to local and neighboring areas or cities. Similarly, this indirectly leads to an increase in energy demanded by the national economy in economically developed areas and neighboring areas, and an increase in CE in these areas (Lui et al., 2021). Although China has been advocating CE reduction strategies and industrial structure upgrading in recent years, the share of the tertiary industry, which emits less CO_2, in the industrial structure shows an increasing trend, which leads to the secondary industry, which emits more CO_2, still showing a higher share, with obvious regional differences. On the whole, the dividend of industrial structure adjustment has not been well performed, because IND and ISU have a positive impact on CE at the 1% significance level [67,68]. In addition, the neighborhood effect of RET is diametrically opposed to ER, i.e., the spatial spillover effect of RET ($W_x \times \ln RET$) has a coefficient of 0.171 and a negative sign at the 1% level of significance. This indicates that an improvement in RET can significantly reduce CE in neighboring areas, although it does not contribute to the local environmental quality [69]. Specifically, a 1% increase in the level of local RET will result in a 0.171% reduction in CE in the surrounding area. This is opposite to the results of [40] for China and [70] for South America, who found that

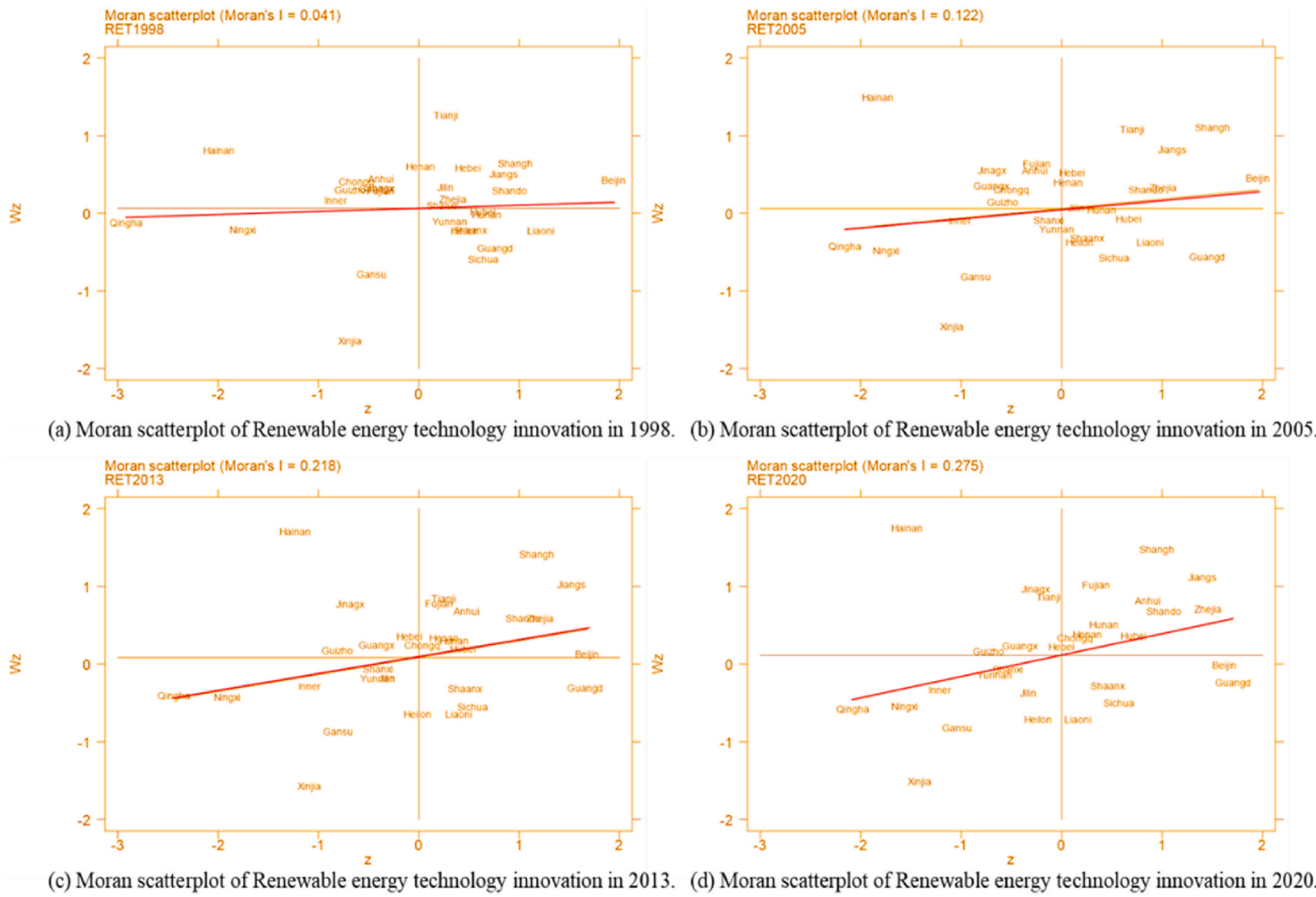


Fig. 3. Moran scatterplot of RET.

Table 4
Spatial model test results.

Test	Index	Statistics	P value
LM test	LM Lag test	6.739***	0.009
	R-LM Lag test	3.037*	0.081
	LM-Error test	5.590**	0.018
	R-LM-Error test	1.888	0.169
Wald test	Wald SAR	78.15***	0.000
	Wald SEM	52.61***	0.000
LR test	LR SAR	14.52**	0.024
	LR SEM	17.45***	0.008

Note: ***, ** and * denote that the coefficient of the variable has been tested for significance at 1%, 5% and 1%.

RET only suppressed CE in the surrounding region. Overall, the carbon reduction effect of ER will be gradually highlighted with the improvement of regional RET, i.e., the "forced abatement effect" of ER will start to be highlighted, gradually offsetting the "green paradox effect" negative impact of ER [71].

Finally, models 5–7 give the decomposition of spatial effects based on the SDM model, including direct, indirect and total impacts. In terms of impact paths, the direct, indirect and total impacts of ER, RET, Pgdp, URB and ISU are based on the same paths as the fixed effects, but the impact of RET is variable. Specifically, RET significantly exacerbates local environmental pollution, but can significantly improve the environmental quality of surrounding neighboring areas, and the total effect is −0.088 at 1% significance level. This indicates that RET is generally beneficial to improve the environmental quality of all regions in China after considering spatial factors, while ER exacerbates environmental pollution, which is consistent with the case where spatial effects are not considered [72]. Therefore, on a region-wide basis, RET makes a significant contribution to the reduction of CE. Moreover, the direct and indirect effects of ER and RET accounted for 46.36% (19.63%) and 53.64% (80.37%) of the total effect in the SDM model, respectively, indicating that ER and RET have a significant spatial effect and have a greater inhibitory effect on CE in the surrounding neighborhoods than on the local ones without affecting local economic development conditions [64]. In conclusion, the total effect is beneficial to reduce CE because CE has external economies of scale and regional heterogeneity, so that the marginal CE of enterprises will be reduced as the intensity of ER increases [73], i.e., ER pushes enterprises to reduce emissions. As illustrated by Refs. [47,74]; the increase of ER intensity can force green RET, and the progress of renewable energy technology is beneficial to reduce CE, i.e., environmental regulation → renewable energy technology innovation → CO_2 emissions.

4.4. Nonlinear effect analysis

In earlier studies, the impact of either ER or green (renewable energy) technology innovation on CE has not been uniformly concluded so far, as it may be positive or negative, or may have no significant effect. However, this study suggests that the difference in the level of regional green economy sustainability may be related to the non-linear relationship between ER, RET and CE. The main reasons are: (1) The higher the level of regional economic development, the stronger the siphoning effect, which leads to the obvious contagiousness and emulation of ER in the region. (2) The level of RET has strong regional differences and heterogeneity, that is, when the higher the level of Pgdp, the more the

Table 5
Spatial panel regression results.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	FE	SEM	SAR	SDM	Direct Effect	Indirect Effect	Total Effect
$W_x \times$ lnER				0.085** (2.20)			
$W_x \times$ lnRET				−0.171*** (−2.84)			
lnER	0.171*** (6.12)	0.068*** (2.57)	0.788*** (3.26)	0.061** (2.30)	0.078*** (2.82)	0.200*** (3.09)	0.278*** (3.71)
lnRET	−0.064** (−2.26)	−0.121*** (−3.03)	−0.062* (−1.80)	0.128*** (2.64)	0.110** (2.43)	−0.198** (−2.28)	−0.088* (−0.95)
lnPgdp	0.416*** (6.64)	0.058 (0.72)	0.039 (0.58)	0.178 (1.35)	0.198* (1.66)	0.085 (0.50)	0.284 (1.75)
lnURB	0.387*** (4.09)	−0.097 (−0.94)	−0.077 (−0.72)	−0.015 (−0.14)	0.035* (0.29)	0.634 (1.59)	0.668** (1.41)
lnIND	−0.115* (−1.11)	0.521*** (3.67)	0.553*** (4.04)	0.484*** (3.32)	0.542*** (3.52)	0.707 (1.37)	1.249** (2.10)
lnISU	0.286*** (3.55)	0.349*** (3.98)	0.365*** (4.23)	0.387*** (4.11)	0.435*** (4.29)	0.497* (1.45)	0.933** (2.37)
C	−3.881*** (−7.30)						
Hausman	49.56***						
N	690	690	690	690			
Spatial λ/ρ		0.469*** (11.66)	0.461*** (11.72)	0.474*** (18.16)			
σ^2		0.1538*** (18.18)	0.154*** (18.21)	0.150*** (18.16)			

Notes: (1) Values in parentheses are t-statistics; (2) ***, **, and * denote that the coefficients of the variables have passed the significance tests of 1%, 5%, and 10%, respectively.

region pays attention to environmental and economic sustainability, and thus increases the proportion of investment in green energy (renewable energy) technology innovation to meet the demand for sustainable development, and vice versa. (3) The improvement of ER intensity, on the other hand, will discourage the entry of highly polluting companies and thus inhibit foreign capital, but it will also facilitate the inflow of green capital, such as GTI (Green Technology Innovation) and RET, when the industrial structure of the district is optimized and upgraded, and the energy-saving and emission-reduction effects become apparent. To test the above hypothesis, this study uses the economic development level of each region in China as the threshold and constructs single, double and triple threshold models based on threshold sampling 600 times to examine the non-linear relationship between ER and RET and CE. Table 6 shows the results of the threshold effect test. According to Table 6, when the Pgdp is below the thresholds of 9.126 and 8.790, the coefficients of ER and RET effects on CE are 0.234 and −0.381, respectively, and are significant at the 1% significance level. This indicates that for every 1% increase in the intensity of ER when the economic development level of the region is below the threshold (9.126), the CE increases by 0.234%. However, the opposite is true for RET, as each 1% increase in the level of RET reduces CE by 0.381% when the region's economic development is below the threshold (8.790). When the economic development level of the region is higher than the threshold value of 9.126 and 8.790, respectively, each 1% increase in the intensity of ER and the level of RET reduces CE by 0.347% and 0.188, respectively. This suggests that the higher the economic development level, the more favorable the ER is to achieve carbon emission reduction and improve environmental quality [75], but the RET is significantly reducing its role to reduce CE as the economic development level increases, i.e., the marginal emission reduction from firms investing capital in renewable energy technologies is diminishing when the economy is highly developed. Meanwhile, this also indirectly contributes to the more significant emission reduction effect of RET in relatively less developed regions [64,65]. It can be seen that the ER compensates for the RET.

Table 6
Results of the threshold effect test.

Threshold estimation		Threshold value	Threshold estimation	Threshold value
Regression results of the panel threshold of lnER on lnCE				
F-value	Single	14.98*	lnER*I(Th < q)	0.234****
	Double	31.44**		
	Triple	11.48	lnER*I(Th ≥ q)	−0.347****
Threshold	q	9.126		
Coefficient	lnRET	0.157***	lnIND	0.490***
	lnURB	−0.091	lnISU	0.401***
Regression results of the panel threshold of lnRET on lnCE				
F-value	Single	8.31*	lnRET*I(Th < q)	−0.381***
	Double	10.10		
	Triple	5.34	lnRET*I(Th ≥ q)	−0.188***
Threshold	q	8.790		
Coefficient	lnER	0.094***	lnIND	0.557***
	lnURB	−0.058	lnISU	0.409***

Note: ***, **, and * represent statistical significance of coefficients at 1%, 5%, and 10%, respectively.

4.5. *Robustness test*

Considering the sensitivity of the spatial weight matrix, to ensure the reliability and soundness of the findings further, this study further examines the effects of ER and RET on CE in the framework of geographic proximity moment and economic proximity matrix by changing the measures of the core variables, such as using the expenses of pollution control equipment and revenues from emission fees to measure the ER intensity and the knowledge stock of per capita RET (see Table 7). According to the results of the robustness estimation in Table 7, both the measures of the replacement core explanatory variables and the effects of the replacement spatial weight matrices ER and RET on CE are basically consistent with the above results, and despite the different coefficients of the estimation results, there is no fundamental change in their directions and significance levels, which indicates the robustness

Table 7
Robustness test.

Variable	Change Measurement Method		Replace the Space Matrix	
	FE	SDM	Geographic Proximity Matrix	Economic Proximity Matrix
lnER	0.109*** (3.97)	0.449* (1.71)	0.060** (2.23)	0.171*** (6.12)
lnRET	−0.134*** (−3.45)	−0.157*** (−3.29)	−0.077*** (−0.87)	−0.064** (−2.26)
$W_x \times$ lnER		0.078** (2.07)	0.022** (0.35)	0.048* (1.31)
$W_x \times$ lnRET		−0.061* (−1.26)	−0.220** (−2.33)	−0.391*** (−4.19)
Spatial ρ		0.463*** (11.54)	0.674*** (12.19)	0.654*** (11.12)
Control	Yes	Yes	Yes	Yes
N	690	690	690	690

Note: *** denotes that the coefficients of the variables has passed the 1% significance test.

and reliability of the study results. Similarly, the direction and significance level of the regression coefficients of the effects of either the geographic proximity matrix or the economic proximity matrices ER and RET on the local and surrounding neighborhood CE did not change fundamentally after the introduction of the spatial matrix compared to the spatial econometric regressions described above, i.e., the estimated results of this present study are sound and reliable.

5. Conclusions and policy implications

This study systematic analyzed the effects of ER and RET on CE directly and indirectly based on panel data of 30 Chinese provinces from 1998 to 2020 and using spatial econometric models in both theoretical and empirical dimensions. The results show that RET significantly reduces CE in all regions of China, and the effect of RET on local emission reduction is much greater than that on neighboring regions after considering the spatial effect, which also highlights the "radiation effect" and "diffusion effect" of RET (Irfan et al., 2022). However, ER significantly contributes to CE, and their contribution to the local area is much smaller than that of the neighboring areas. The possible reason for this is the existence of mutual imitation or emulation behavior of regional ER, i.e., when the higher the level of economic development the higher the intensity of ER, thus contributing to the reduction of CE. This is consistent with the findings of [22–24]. On the contrary, when the level of economic development is low or backward, the greater the intensity of ER has less effect on reducing CE, because it is when the level of economic development exceeds a certain threshold value (9.126) that ER reduces CE and contributes to environmental improvement [26,27]. However, the opposite is true for RET, as the reduction effect of RET decreases with the increase of regional economic development, which indirectly indicates that excessive ER will inhibit RET and validate the "constraint theory" [64]. Thus, the significance and magnitude of the carbon reduction effect of ER and RET depends on the economic development level of each region [71]. Therefore, in response to environmental climate change, local governments should formulate relevant ER (laws and regulations) from multiple perspectives and dimensions, and use a combination of ER and RET to maximize the effect of energy saving and emission reduction without affecting the local economic development level. In addition, another important question derived from the findings of this study is that since the carbon reduction effects of ER and RET are constrained by the level of regional development, will the incentive policies of ER and RET also depend on the level of regional economic development? The study of this question can help further explore how to optimize the policies related to RET, which is a work worthy of further exploration.

Based on the above findings, promoting technological innovation in renewable energy in each region of China and reasonably optimizing the intensity of ER to prevent the increase of CE intensity is one of the most effective ways to achieve the reduction of CE and is also the basis for sustainable regional economic development. To this end, this study proposes the following policy recommendations. Firstly, according to the condition of each region, the intensity of ER should be appropriately strengthened according to local conditions, and the ER tools should be reasonably selected, and at the same time, we should be alert to the following behaviors of unrealistic and blind increase of ER intensity, so as to avoid the "restructuring" phenomenon of the impact track of ER on CE, i.e. inverted N type, which will trigger the green paradox effect again. Secondly, to give full play to the CE reduction effect of ER, it is also necessary to choose reasonable ER tools. Environmental standards, emission limits and other "control" environmental regulatory tools lack sufficient incentives for enterprises due to their strong mandatory nature, while "incentive" environmental regulatory tools, such as emissions trading and environmental subsidies, provide continuous incentives for enterprises to innovate in renewable energy technologies, which are conducive to improving the efficiency of enterprises' pollution control. Thirdly, improve the regional RET system and narrow the regional RET gap. At the same time, it is also necessary to increase investment in RET, increase financial and taxation support, promote the transformation of renewable energy technology achievements and optimize resource allocation efficiency, improve the level of renewable energy technology progress, promote the transformation and upgrading of green industries, and promote sustainable economic and environmental development.

In addition, in this study, the empirical analysis was conducted based on the level of economic development of each region and other implied variables were ignored, so this can be considered as the most significant research limitation. Another limitation of the current study is the sample selection and the econometric approach, as this study was conducted using a spatial econometric approach for the panel data of 30 Chinese provinces only. Therefore, future research can select samples from different countries on this basis, such as developed economies, developing economies and underdeveloped economies for comparative study, and control variables as far as possible include income inequality, regional differences, system, labor population, education quality, financial development, environmental governance, ecological footprint indicators and other indicators affecting environmental quality and economic development, so as to deeply study and investigate this relationship from multiple dimensions and angles.

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Ethic statement

Not applicable.

Consent for publication

The article is original, has not already been published in a journal, and is not currently under consideration by another journal.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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